

Contents lists available at [SciVerse ScienceDirect](http://SciVerse.ScienceDirect.com)

International Journal of Forecasting

journal homepage: www.elsevier.com/locate/ijforecast

Forecasting monetary policy rules in South Africa

Ruthira Naraidoo^{a,*}, Ivan Paya^b^a Department of Economics, University of Pretoria, Pretoria, 0002, South Africa^b Department of Economics, Lancaster University, Lancaster University Management School, LA1 4YX, UK

ARTICLE INFO

Keywords:

Taylor rules
Nonlinearity
Nonparametric
Semiparametric
Forecasting

ABSTRACT

This paper is the first one to: (i) provide in-sample estimates of linear and nonlinear Taylor rules, augmented with an indicator of financial stability, for the case of South Africa, and (ii) analyse the ability of linear and nonlinear monetary policy rule specifications, as well as nonparametric and semiparametric models, to forecast the nominal interest rate setting that describes the South African Reserve Bank's (SARB) policy decisions. Our results indicate, first, that asset prices are taken into account when setting interest rates; second, that there are nonlinearities in the monetary policy rule; and third, that forecasts constructed from semiparametric models perform particularly well over the inflation targeting regime and that there are gains from semiparametric models in forecasting the interest rates as the forecasting horizon lengthens.

© 2011 International Institute of Forecasters. Published by Elsevier B.V. All rights reserved.

1. Introduction

Six times a year, approximately every 8 weeks and sometimes more often, the South African Reserve Bank (SARB) announces its target for the key lending rate, the repo rate, which is the price at which the central bank lends cash to the banking system. The Reserve Bank's target for the repo rate is one of the most anticipated and influential decisions which regularly affects financial markets, and is of interest to economic analysts, economic forecasters and policymakers. We first conjecture that this monetary policy decision can be described within the general form of Taylor rule models, for a number of reasons. First, the SARB has a mandate to achieve and maintain price stability, in the interest of balanced and sustainable economic growth, and therefore output/employment stability. Second, the Monetary Policy Committee (MPC) of the South African Reserve Bank (SARB) has formulated its policy in terms of the repo rate since 1998. This issue is especially relevant and is currently being debated in the case of South Africa,

which has undergone important changes in its monetary policy settings over the last two decades. These reforms include central bank independence and the introduction of inflation targeting of 3%–6% in 2000, having moved from a constant money supply growth rate rule which was first set in 1986.

The general benchmark of monetary policy rules has been the subject of intense debate over the last few years, as recent economic events have turned attention to the behaviour of certain asset prices (stock prices, house prices, exchange rates), and also as a result of the concern of central banks with respect to the maintenance of financial stability (see e.g. [Bernanke & Gertler, 2001](#)). This is in line with the current debate on central banks having additional objectives over and above inflation and output stabilisation ([Walsh, 2009](#)). If such is the case, it is most likely that the monetary policy reaction function will respond to those variables once they reach certain 'unsustainable' levels, as opposed to when they follow their 'fundamental' path. This could indeed be the case with the SARB, because its other primary goals, as defined in the Constitution, are to protect the value of the currency and achieve and maintain financial stability. [Woglom \(2003\)](#), in his discussion of how the introduction of inflation targeting in 2000 affected monetary policy in

* Corresponding author. Tel.: +27 12 420 3729; fax: +27 12 362 5207.

E-mail addresses: ruthira.naraidoo@up.ac.za (R. Naraidoo),
i.paya@lancaster.ac.uk (I. Paya).

South Africa, points out that the response of the SARB to changes in the real value of its currency are far from clear, and are therefore a source of confusion.¹ It is also worth noting that South African financial institutions experienced no direct exposure to the sub-prime crisis in terms of interbank or liquidity problems of the type experienced in developed countries (see e.g. Mminele, 2009). The first contribution of this paper is therefore to examine whether asset prices are one of the determinants of interest rate setting by the SARB in the in-sample estimates. The fact that we combine three different asset prices to give a single index complements the work by Woglom (2003), where only changes in the real effective exchange rates are included in the determinants of the rule.

The second contribution is to analyse whether the Taylor rule followed by the SARB, with or without asset prices, displays a nonlinear functional form. Recent research has theoretically demonstrated the possibility that a central bank might not follow a linear reaction function. Asymmetric preferences (e.g. a linex function, as in Nobay & Peel, 2003) impose a higher cost on overshooting the inflation target than undershooting it. The opposite would be true for the output gap if booms are thought of as being less costly than slumps. Aksoy, Orphanides, Small, Weiland, and Wilcox (2006) show that, under the opportunistic approach to disinflation, the policymaker would not respond actively to any deviation of inflation from the target. The policymaker concentrates on output stabilisation for sufficiently small deviations, and will only act to bring inflation down when it exceeds a certain threshold.

A nonlinear policy rule also results from assuming a nonlinear Phillips curve. To the extent that nominal wages are downwardly inflexible, inflation is a convex function of the unemployment rate (see e.g. Layard, Nickell, & Jackman, 1991). This, by Okun's law, means that inflation is also convex in the output gap. The nonlinear aggregate supply, combined with a quadratic loss function, leads to a policy rule where the response of interest rates to inflation is higher (lower) when inflation is above (below) target. For example, Surico (2007) argues that the response to inflation may be higher in periods of poor economic performance, while Cukierman and Muscatelli (2008) find that the opposite is true. Given the above strand of the literature, we therefore try to shed some light on the specification of the particular monetary policy rule in South Africa.

Finally, we contribute to the sparse body of literature that uses Taylor rules to forecast the nominal interest rate out-of-sample. Some notable exceptions are Qin and Enders (2008) and Moura and de Carvalho (2010). The former use US data to compare the in-sample and out-of-sample properties of linear and nonlinear Taylor rules for different monetary policy regimes. The

latter examine different specifications of Taylor rules in terms of their out-of-sample performances for the seven largest Latin American economies. In this study about South Africa, we construct the forecasts from linear and nonlinear parametric models, as well as from the more flexible nonparametric and semiparametric models under three alternative expectations formations for the target variables, and examine their forecasting gains. Furthermore, it is well known that significant in-sample evidence of predictability does not guarantee a significant out-of-sample predictability. There could be a number of reasons for this, such as the power of tests (Inoue & Kilian, 2004). We therefore provide both in-sample and out-of-sample results in order to shed some light on the specification of the SARB policy rule and provide guidance on models for forecasting interest rates in SA.

2. Taylor rules

2.1. Benchmark linear Taylor rule

Existing studies of the impact of inflation and output on monetary policy use a version of the Taylor rule (Taylor, 1993) which allows for interest rate smoothing (Clarida, Gali, & Gertler, 1998, 2000) and assumes that the actual nominal interest rate, i_t , adjusts towards the desired rate, i_t^* , as follows:

$$i_t = \alpha_i(L)i_{t-1} + (1 - \alpha_i)i_t^*, \quad (1)$$

where $i_t^* = \bar{i} + \alpha_\pi E_t(\pi_{t+p} - \pi^*) + \alpha_y E_t(y_{t+p} - y^*) + \alpha_l E_t(I_{t+p} - I^*)$, with i_t^* being the desired nominal interest rate, \bar{i} the natural interest rate, $E_t \pi_{t+p}$ the expected inflation rate at time $t + p$, π^* the inflation target, $E_t(y_{t+p} - y^*)$ the expected output gap at time $t + p$, $E_t(I_{t+p} - I^*)$ the expected financial indicator gap used to augment the original rule, α_π the weight on inflation, α_y the weight on the output gap, and α_l the weight on an index I of financial variables such as exchange rates, house prices, stock prices and other financial variables. $\alpha_i(L) = \alpha_{i1} + \alpha_{i2}L + \dots + \alpha_{in}L^{n-1}$ is the lag polynomial in the interest rate, showing interest rate persistence and smoothing.² We can thus write our benchmark linear model as:

$$i_t = \alpha_o + \alpha_i(L)i_{t-1} + (1 - \alpha_i)[\alpha_\pi E_t \pi_{t+p} + \alpha_y E_t(y_{t+p} - y^*) + \alpha_l E_t(I_{t+p} - I^*)] + \varepsilon_t, \quad (2)$$

where $\alpha_o = (1 - \alpha_i)(\bar{i} - \alpha_\pi \pi^*)$ and ε_t is an error term. Eq. (2) represents a constant proportional response to inflation, output and financial indicator gaps. The theoretical basis for the linear Taylor rule (Eq. (2)) comes from the assumption that policymakers have a quadratic loss function and that the aggregate supply or Phillips curve is linear.

¹ A different approach to the one used in our paper, and in the literature cited here, is the analysis by Knedlik (2006) of the effect of real exchange rate deviations on the design of monetary policy rules in SA. In Knedlik's case, optimal rules should provide optimal monetary conditions (internal stability), and should avoid the volatility of capital flows (external stability). Such rules are derived from the estimation of the parameters of the estimated Monetary Conditions Index (MCI).

² We use a lag polynomial of order two in our estimation. These are determined according to the AIC, and we note that a model with one lag of the interest rate suffers from serial correlation.

2.2. Benchmark nonlinear Taylor rule

We noted above that the focus of the monetary policy literature has increasingly been placed on the nonlinear models resulting from asymmetric central bank preferences (e.g., Nobay & Peel, 2003), the nonlinear (convex) aggregate supply or Phillips curve (e.g., Dolado, Maria-Dolores, & Naveira, 2005), or the opportunistic approach to disinflation (Aksoy et al., 2006). The following model has been suggested to parametrically capture those nonlinearities in the policy rules:

$$i_t = \alpha_0 + \alpha_i(L)i_{t-1} + (1 - \alpha_i)R_{1t} + \lambda_t(1 - \alpha_i)R_{2t} + \varepsilon_t, \quad (3)$$

where $R_{1t} = \alpha_{1\pi}E_t(\pi_{t+p} - \pi^*) + \alpha_{1y}E_t(y_{t+p} - y^*) + \alpha_{1l}E_t(l_{t+p} - l^*)$ and $R_{2t} = \alpha_{2\pi}E_t(\pi_{t+p} - \pi^*) + \alpha_{2y}E_t(y_{t+p} - y^*) + \alpha_{2l}E_t(l_{t+p} - l^*)$, and λ_t is a nonlinear function. The nonlinear function λ_t can take a number of specifications, such as a threshold specification (Bec, Ben Salem, & Collard, 2002), or a smooth one where the response of the interest rate differs between two inflation regimes (higher than γ^π , and lower than γ^π):

$$\lambda_t(E_t\pi_{t+p}; \theta, \gamma^\pi) = \frac{1}{1 + e^{\theta(E_t\pi_{t+p} - \gamma^\pi)/\sigma_{E_t\pi_{t+p}}}}. \quad (4)$$

In Eq. (4), the transition function λ_t is continuous and is bounded between zero and one in the transition variable $E_t\pi_{t+p}$. As the transition variable tends to ∞ , λ_t tends to 0, and as the transition variable tends to $-\infty$, λ_t tends to 1. The smoothness parameter θ determines the smoothness of the transition regimes.³

2.3. Nonparametric and semiparametric specifications

We show above that monetary policy settings have been highly variable, so that even the linear and nonlinear parametric models might have trouble uncovering the true data generating process of the interest rate. Rather than assuming that the functional form is known, nonparametric and semiparametric methodologies substitute less restrictive assumptions, such as smoothness and moment restrictions.

To this end, we carry out the Nadaraya-Watson local constant regression estimator and consider a more popular extension, namely, the local linear regression method (Li & Racine, 2004). We use two selection methods to choose the correct amount of local averaging (bandwidth selection), namely the least-squares cross validation of Hall, Racine, and Li (2004) and the AIC method of Hurvich, Simonoff, and

Tsai (1998).⁴ More precisely, the nonparametric model for the monetary policy rule is given by

$$i_t = f((L)i_{t-1}, E_t\pi_{t+p}, E_t(y_{t+p} - y^*), E_t(l_{t+p} - l^*)) + \varepsilon_t, \quad (5)$$

where $f(\cdot)$ represents a function which is not known to lie within any particular parametric family.

Semiparametric models are a compromise between fully nonparametric and fully parametric specifications. They are formed by combining parametric and nonparametric models in order to reduce the curse of dimensionality of nonparametric models. We employ a popular regression-type model, namely the partially linear model of Robinson (1988):

$$i_t = \alpha_i(L)i_{t-1} + f(E_t\pi_{t+p}, E_t(y_{t+p} - y^*), E_t(l_{t+p} - l^*)) + \varepsilon_t, \quad (6)$$

where $\alpha_i(L)$ is a vector of unknown parameters to be estimated and the functional form of $f(\cdot)$ is not specified.

3. Data

3.1. Data discussion

Our analysis is monthly and spans the period from 1986:01 to 2008:12. The variables are described in the Appendix and displayed in Fig. 1.⁵ The sample period corresponds roughly to two monetary regimes.⁶ In February 2000, the Ministry of Finance announced in the Budget speech that the government had decided to set an inflation target range of 3%–6%. Before this announcement, informal inflation targeting was already being applied by the SARB, with a target range of 1%–5% for core inflation from 1998 onward.

We construct a financial indicator index (I_t) which is designed to capture misalignments in the financial markets. We compute I_t using a weighted average of the annual percentage rate of change of the nominal exchange rate of the rand against the US dollar (ge_t), real share prices (gs_t), and real property prices (gh_t). In particular, the weights for the exchange rate, stock price and property price changes are 0.6, 0.3, and 0.1, respectively. This follows on from the fact that a preliminary analysis of the individual series suggests that, in general, the exchange rate was the most significant financial indicator, followed by share prices, and finally by house prices.⁷ It is also

⁴ These methods can be found in the R np package of Hayfield and Racine (2008).

⁵ We note that a preliminary analysis suggests that the inflation series follows a nonstationary process. The ADF and PP unit root tests do not reject the null, with p -values of around 0.13. However, in line with common practice, inflation is treated as stationary.

⁶ Under the cash reserves system, pre-announced monetary targets were first used in 1986, to be achieved indirectly through adjusting interest rates. We choose this particular period because it is difficult to estimate stable policy rules using data from before 1986, when the Reserve Bank switched to using the interest rate as the main instrument of monetary policy.

⁷ We note that it is difficult to provide a precise explanation for this exact figure of the significance of each variable, given that we examine many different regression specifications and time periods.

³ Note that the response of interest rates to the lagged interest rate is linear in these models, and that nonlinear policy rules can be defined using the output gap or the financial index as possible transition variables in the weighting function (Eq. (4)). Alternatively, one can use the quadratic logistic function, as did Martin and Milas (2004). These nonlinear models were also considered in the current paper, but we do not report the results due to their poor fits.

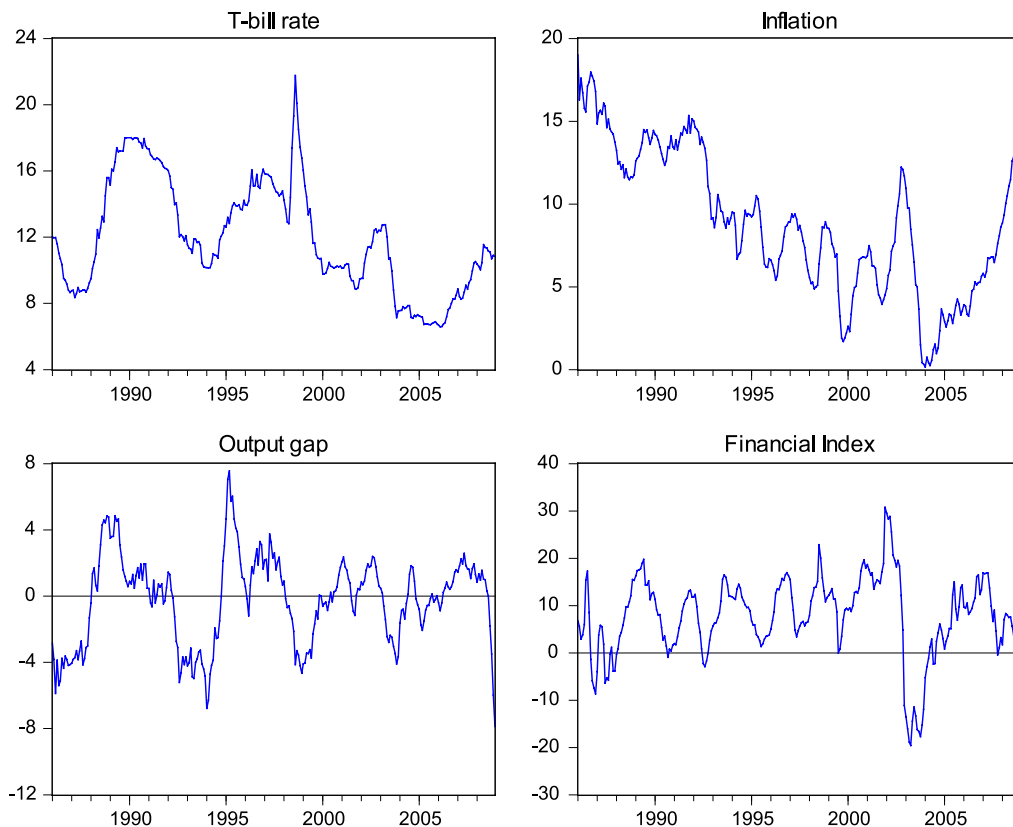


Fig. 1. Evolution of the main variables.

worth noting that using a financial indicator index rather than including the variables in the interest rate rule separately is in line with the findings of Castro (2008), who argues that, rather than attempting to target different asset prices, central banks could be monitoring asset prices and financial information in the form of a composite financial index.⁸

3.2. Expectations formation

We resort to three ways by which the private sector can form its expectations of inflation, the output gap and the financial indicator gap. For the 'forward-looking' case, we use a perfect foresight model by replacing the expected future variables at time $t + 1$ with their actual one-period-ahead values and then estimate it using the Generalised Method of Moments (GMM); that is, $E_t \pi_{t+1} = \pi_{t+1}$, $E_t(y_{t+1} - y^*) = y_{t+1} - y^*$ and $E_t(I_{t+1} - I^*) = I_{t+1} - I^*$. For the 'backward-looking' case, we use the first lag of all three variables as a measure of the one-period-ahead

expectation, $E_t \pi_{t+1} = \pi_{t-1}$, $E_t(y_{t+1} - y^*) = y_{t-1}$, $E_t(I_{t+1} - I^*) = I_{t-1} - I^*$.⁹

We employ a learning rule for the third expectation formation process. After experiencing high inflation for a long period of time, there may be good reasons for the private sector not to fully believe the disinflation policy (see also Bomfimm & Rudebusch, 2000). In his discussion of endogenous learning, King (1996) says that it might be rational for the private sector to suppose that, in trying to learn about the future inflation rate, many of the relevant factors are exogenous to the path of inflation itself. In light of this, King assumes that private sector inflation expectations follow a simple rule which is a linear function of the inflation target and the lagged inflation rate. In this respect, we model the one-period-ahead expected inflation as $E_t \pi_{t+1} = \rho \pi^T + (1 - \rho) \frac{1}{12} \sum_{i=1}^{12} \pi_{t-i}$ (where ρ captures the credibility of the new regime, which we set at $\rho = 0.5$, and $\pi^T = \frac{\pi^L + \pi^U}{2}$ is an average of the two pre-announced bands, $\pi^L = 3\%$ and $\pi^U = 6\%$). This rule implies that agents use the target inflation rate, π^T , and past information to form their view of what inflation will be in the next period.¹⁰

⁸ An initial in-sample analysis (in terms of the regression standard error and R^2 values) of the parametric linear and nonlinear models does not suggest the superiority of the model with separate variables relative to the model with the composite index. We decided to be as parsimonious as possible with the number of variables in the forecasting exercise, and therefore used the composite index.

⁹ We tried various different specifications, and the first-period-ahead for the 'forward looking' model and the first lag for the 'backward looking' model provided the best information criteria. Dating the variables at time t as in Taylor's seminal paper was also implemented, but the results were quantitatively similar.

¹⁰ The choice of the parameter ρ is somewhat *ad hoc*. Some sensitivity analyses where we tried lower values than 0.5 on target inflation changed

Overall we have twelve models: four policy rules, linear and nonlinear, together with alternative flexible nonparametric and semiparametric models, and three types of expectation formation for each of those models. We denote Models 1–3 to be the linear Taylor rule version of Eq. (2), Models 4–6 the nonlinear Taylor rule version of Eq. (3), Models 7–9 the nonparametric version of Eq. (5), and Models 10–12 the semiparametric version of Eq. (6).

3.3. In-sample analysis

In order to keep the in-sample analysis brief, we only report a subset of the models which will be used for forecasting purposes in the rest of the paper. In particular, Table 1 presents the results for the in-sample estimates of Eqs. (2) and (3) in the case of backward-looking expectations for two different periods: the whole sample (1986–2008) and the inflation targeting period (2000–2008). A few results are worth mentioning. First, nonlinear Taylor rules are not rejected by the data, especially for the latter period, where the SARB explicitly targeted inflation. We can infer from the nonlinear estimates that, as inflation increases, the response from the Reserve Bank to both inflation and the output gap is more aggressive.¹¹ Similar results are found by Castro (2008) for the cases of the ECB and the Bank of England, but not for the Fed. Our estimates suggest that there is some evidence of a deflation bias to monetary policy, as the response to inflation is larger when inflation exceeds the 4.56% estimated target. However, it should be noted that the inflation effect is lower than one, and therefore does not satisfy the ‘Taylor principle’ that inflation increases trigger an increase in the real interest rate. Similar results of the inflation effect being lower than one for the case of South Africa have been noted by Woglom (2003) and Naraidoo and Gupta (2010). The latter paper used the quadratic logistic function and noted that the response of monetary policy to inflation is nonlinear, as interest rates respond more when inflation is further from the target zone. Hayat and Mishra (2010), using a semiparametric model, find that the Fed’s monetary policy has only reacted significantly to changes in inflation when they were between approximately 6.5%–8.5%, in the post-war period.

Second, the financial indicator index seems to play a role, though not a prominent one, in the monetary policy reaction function of the SARB.¹² This is also in line with the findings of Castro (2008) for the case of the ECB,

some results, in the nonlinear Taylor rule estimation in particular. It seems that as the transition variable becomes smoother, and ρ (a moving average of past inflation) lower, the nonlinearity gradually disappears.

¹¹ This result is also illustrated in Fig. 2, where we plot the transition function, λ_t in Eq. (4), together with the inflation rate. λ_t fluctuates between 0 and 1, depending on the level of inflation, meaning that the response of the SARB to its target variables varies according to the deviations of inflation from the target $\hat{\gamma}^\pi (= 4.56)$.

¹² Financial conditions can indeed be closely related to inflation movements (see D’Agostino & Surico, 2009). A Granger causality test between inflation and our financial indicator index (I_t) shows causality running from the financial conditions index to inflation. The contemporaneous correlation between the two series is not significantly

Table 1

In-sample estimates of linear and nonlinear Taylor rules.

$i_t = \beta_1 i_{t-1} + \beta_2 i_{t-2} + (1 - \beta_1 - \beta_2)[\alpha_1 + \alpha_\pi \pi_{t-1} + \alpha_y y_{t-1} + \alpha_I I_{t-1}] + (1 - \beta_1 - \beta_2)[\delta_\pi \pi_{t-1} + \delta_y y_{t-1} + \delta_I I_{t-1}] \frac{1}{1 + e^{\theta(\pi_{t-1} - \gamma^\pi)/\sigma_\pi}} + \varepsilon_t$				
Parameter	Linear rule		Nonlinear rule	
	1986–2008	2000–2008	1986–2008	2000–2008
β_1	1.26 (0.13)	1.18 (0.08)	1.24 (0.14)	1.04 (0.11)
β_2	−0.30 (0.13)	−0.26 (0.07)	−0.28 (0.12)	−0.15 (0.10)
α_1	9.01 (1.33)	7.81 (0.68)	4.20 (2.55)	8.90 (0.97)
α_π	0.34 (0.19)	0.47 (0.14)	0.70 (0.21)	0.29 (0.10)
α_y	1.13 (0.28)		2.10 (0.62)	0.72 (0.40)
α_I	0.21 (0.13)	0.11 (0.06)		
δ_π				−1.78 (0.56)
δ_y			−5.49 (2.93)	−1.48 (0.75)
δ_I			0.75 (0.57)	0.31 (0.13)
θ			0.67 (0.37)	1.74 (0.71)
γ^π			[0.10] 6.22 (2.13)	[0.05] 4.56 (1.34)
AIC	1.43	0.65	1.42	0.59
se	0.489	0.327	0.485	0.312

Figures in brackets are HAC standard errors. Figures in square brackets are bootstrapped p -values under the null of a linear model. We only report coefficients for variables that are significant at the 10% level at least.

which he argues made the Eurozone less vulnerable to the recent credit crunch. Our nonlinear estimates suggest that ‘financial disequilibria’ are addressed explicitly by monetary policy when inflation is not too high, otherwise the focus is on inflation deviations from the target and the output gap.¹³

Third, the parameters of the monetary policy rule seem to change over time. For instance, according to the linear rule, the SARB did not respond to the output gap in the inflation target (IT) period, while it did so before IT. A similar, but not identical, inference can be made from the nonlinear Taylor rule. In that case, the output gap is significant but with a decreasing coefficient, and the

different from zero, but there exist significant correlations between inflation and the lagged $I_t(I_{t-k})$. A rolling correlation coefficient between inflation and I_{t-k} (up to 12 lags, $k = 12$) shows that the correlation between the series increased significantly in the later period of our sample. More complex relationships between these two series will be the subject of further research.

¹³ We have estimated various linear and nonlinear parametric models which exclude the financial indicator index. However, the index appears to be significant in the in-sample results, and the goodness-of-fit statistics suggest that they do play a role. This could also be put into the context of Rudebusch (2002), who points out that the significance of interest rate persistence in the policy rule could be due to a financial spread variable being omitted from the estimated regression. Gerlach-Kristen (2004) find that the inclusion of a financial spread reduces the empirical importance of interest rate smoothing. Bearing this in mind, our empirical models which exclude the financial index variable exhibited a higher interest rate persistence, providing some support for an omitted variable problem.

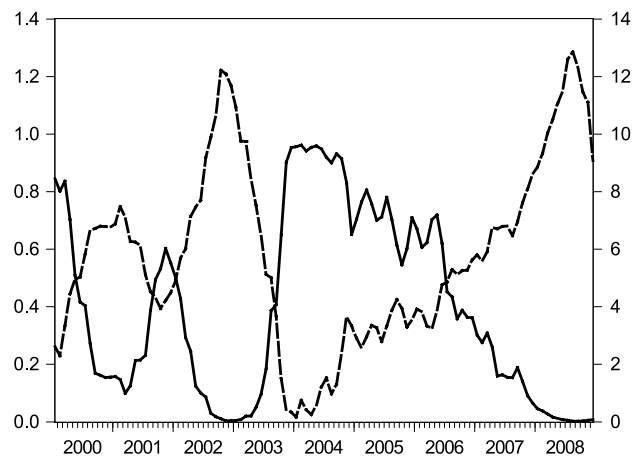


Fig. 2. The solid line represents the transition function λ_t (left scale), and the dotted line represents the inflation rate (right scale).

response of the Reserve Bank to inflation is more gradual, according to its deviations from the target in the latter period.¹⁴

Some of the results which we obtain about the way in which monetary policy has been implemented in SA coincide with those of Woglom (2003) and Naraidoo and Gupta (2010). They also find lower levels of interest rate smoothing, an increased response to inflation deviations and a decreased importance of the output gap in the Taylor rule. On the other hand, Woglom finds no significant response to changes in the real effective exchange rate in the IT period. Two reasons why our results may differ are, first, that our sample for the IT period is considerably longer, and, second, that our financial conditions include changes in the rand-dollar exchange rate, as well as stock and house prices. Lastly, the nonlinear models display lower AIC values than the linear ones. Martin and Milas (2010) also find that nonlinear monetary policy rules provide more in-sample information than their linear counterparts.

It is worth giving a couple of examples in order to put some of our results in the context of recent monetary policy in South Africa. One is the period from 2006 to mid-2007, where the output is close to its potential and inflation is within the target zone, but the financial conditions index is on the rise. Our estimates suggest an increase in the repo rate, which is what actually happened, contrary to what a rule without the asset prices in it would have suggested. The other interesting period is the onset of the global financial crisis in 2008. Despite the fall in the stock market and property prices, the financial index gap is high because of the depreciation of the rand against the dollar. This fact, together with rising inflation, could have contributed to the fact that the SARB kept its policy rate high when faced with the incoming crisis and a negative output gap.

4. Out-of-sample analysis

4.1. Methodology

We use all of the models described in Section 2 as the basis for a repeated forecasting exercise, where we obtain both short- and long-term out-of-sample forecasts based on two types of regression estimation schemes, namely rolling and recursive.¹⁵ The numbers of in-sample and out-of-sample observations are denoted by R and P , respectively, so that the total number of observations is $T = R + P$. In the case of the rolling window, the number of in-sample observations, R , is fixed, and the parameters are re-estimated for each window in order to obtain forecasts up to horizon h . In the recursive scheme, the in-sample observations increase from R to $T - h$ and the parameters of the model are re-estimated by employing data up to time t so as to generate forecasts for the following h horizons. The number of forecasts corresponding to horizon h is equal to $P - h + 1$. The first estimation window in both schemes is 1986:01–1997:12. We calculate one-, three-, six-, and twelve-step-ahead forecasts for the period 1998:01 onwards.

In general, closed-form solutions for multi-step forecasts from nonlinear models are not available. To this end, we employ bootstrap integration techniques (see e.g. Clements & Smith, 1997). The forecast evaluation criteria used are the mean squared prediction error (MSPE) and median squared prediction error (MedSPE). We extend the forecast accuracy analysis by testing the null hypothesis of equal MSPEs between any two competing models, following the methodologies of Diebold and Mariano (1995) and West (1996), with the DM- t statistic, and Clark and West (2007), with the CW- t statistic.

¹⁴ This third result will be dealt with in the forecasting section by using both recursive and rolling window methodologies.

¹⁵ Recent studies suggest that both schemes might be superior at times, depending on the time series and period examined. For instance, Stock and Watson (2005, p. 26) find that “recursive forecasts are more accurate than the rolling forecasts” for the representative macroeconomic dataset they study, while Giacomini and White (2006, p. 1566) find that a “rolling window procedure can result in substantial forecast accuracy gains relative to an expanding window for important economic time series”.

Table 2

Average out-of-sample forecasting ranks.

Model <i>i</i>	(i) MSPE (Recursive)	(ii) MedSPE (Recursive)	(iii) MSPE (Rolling)	(iv) MedSPE (Rolling)
L	1 3.5	3.5	5.75	4.75
	2 5	4.5	9	11.25
	3 5.25	5.75	5.75	5.5
NL	4 3.25	3	11.75	10.25
	5 9.5	10.25	7.25	8.25
	6 6	8.25	10.5	10.5
NP	7 10.75	10.5	5.5	5.75
	8 10.75	9.5	7	6.75
	9 9	8.75	4	5
SP	10 4.75	3.5	6.25	5.25
	11 5.25	5.75	1.75	1.25
	12 5	4.75	3.5	3.5

Columns (i)–(ii) report the average out-of-sample forecasting rank of Model *i* across the recursive windows and forecast horizons $h = 1, 3, 6$ and 12 , using the MSPE and MedSPE criteria. Columns (iii)–(iv) do the same for rolling windows. Model notation: L for linear, NL for nonlinear, NP for non-parametric, SP for semi-parametric. Backward looking models: 1, 4, 7, 10. Forward looking models: 2, 5, 8, 11. Learning models: 3, 6, 9, 12.

The DM-*t* is computed as follows:

$$DM-t = (P - h + 1)^{1/2} \frac{\bar{d}}{\hat{S}_{dd}^{1/2}}, \quad (7)$$

where $\hat{d}_{t+h} = \hat{e}_{1,t+h}^2 - \hat{e}_{2,t+h}^2$, $\bar{d} = (P - h + 1)^{-1} \sum_{t=R}^{T-h} \hat{d}_{t+h} = MSPE_1 - MSPE_2$, $\hat{r}_{dd}(j) = (P - h + 1)^{-1} \sum_{t=R+j}^{T-h} \hat{d}_{t+h} \hat{d}_{t+h-j}$ for $j \geq 0$ and $\hat{r}_{dd}(j) = \hat{r}_{dd}(-j)$, and $\hat{S}_{dd} = \sum_{j=-\bar{j}}^{\bar{j}} K(j/M) \hat{r}_{dd}(j)$ denotes the long-run variance of d_{t+h} , estimated using a kernel-based estimator with function $K(\cdot)$, bandwidth parameter M and maximum number of lags \bar{j} .

A number of issues are worth mentioning. First, multi-step forecasting, $h > 1$, induces serial correlation in the forecast error term, and accordingly, we use Heteroskedasticity and Autocorrelation-Consistent (HAC) estimators (see Clark, 1999). Second, we use the Harvey, Leybourne, and Newbold (1997) small sample bias correction of the estimated variance d_{t+h} and compare the statistic to the Student's *t* distribution with $P - h$ degrees of freedom. Third, the nonlinear Taylor rule given in Eq. (3) nests the linear equation (2), and therefore their population errors are identical under the null hypothesis, making the variance d_{t+h} equal to zero (see McCracken, 2007). However, Buseti, Marcucci, and Veronese (2009) show that the DM-*t* statistic has good size and power properties in certain scenarios.¹⁶ Nevertheless, we employ the Clark and West (2007) test for equal accuracy of nested models. In order to implement this test, we compute

$$\hat{f}_{t+h} = \hat{e}_{1,t+h}^2 - [\hat{e}_{2,t+h}^2 - (\hat{r}_{1,t+h} - \hat{r}_{2,t+h})^2], \quad (8)$$

where $\hat{r}_{i,t+h}$, $i = 1, 2$ are the h -step-ahead point forecasts from models 1 (the restricted model; in our case, the linear) and 2 (the unrestricted model, the nonlinear). The CW-*t* statistic is obtained by regressing \hat{f}_{t+h} on a constant and testing the null hypothesis that the constant equals zero. For $h > 1$, HAC standard errors are used, and the critical values for all horizons are obtained via bootstrap simulation, as was suggested by Clark and West.

4.2. Out-of-sample forecasting comparisons

In Table 2, we begin to compare the forecasts with an overall view of how each individual model ranks against all of the other models across different forecast horizons (one, three, six and twelve months). Columns (i)–(ii) present the average out-of-sample forecasting rankings using recursive windows for the twelve models, according to two evaluation criteria, namely the mean squared prediction error (MSPE) and the median squared prediction error (MedSPE). Columns (iii)–(iv) report our forecasting rankings based on sequences of fixed-length rolling windows.¹⁷ Better or higher-ranked forecasting methods have lower numerical ranks. In examining the average rank results of Table 2, it is useful to note that if the average rank of Model *i* is better than the average rank of Model *j* according to either the MSPE or the MedSPE, then Model *i* outperforms Model *j* according to that particular criterion for more than 50% of the forecast horizons; that is, for at least two of the four forecast horizons used.

We begin by analysing the results obtained using recursive estimates. In this case it is difficult to single out one particular model because a different model dominates the rest for each expectation formation: nonlinear for backward looking expectations, linear for forward looking, and semi-nonparametric for learning. When we consider the rolling window scheme, that is, observations from the early part of the sample are lost as we move into the future, semiparametric models outperform the rest of the models in general, and in the case of forward looking and learning expectations in particular. These results suggest that semi- and non-parametric models do relatively better than parametric ones for the fixed/smaller sample sizes that might be more appropriate in the face of regime changes.

These findings are supported by Tables 3 and 4, which provide a more detailed evaluation of the forecasting performances of each model against alternative models for each forecast horizon ($h = 1, 3, 6$ and 12) and expectations

¹⁶ Buseti et al. (2009) examine the size and power properties of various different forecast accuracy tests for both nested and nonnested models.

¹⁷ The 'average out-of-sample forecasting rank' of a model is computed as an average of the rankings of a particular model across all of its forecasting horizons under a particular evaluation criterion.

Table 3
Forecast accuracy evaluation.

Recursive estimation											
Panel A. Backward looking					Panel B. Forward looking					Panel C. Learning	
Steps ahead					Steps ahead					Steps ahead	
1	3	6	12		1	3	6	12		1	3
L vs.					L vs.					L vs.	
NL	−0.69*	−0.48*	−0.66	−0.90	NL	−0.06	1.35	2.29	0.31	NL	−0.57*
NP	−2.97**	−2.71**	−1.04	−0.03	NP	−3.99**	−2.27**	−1.25	−0.46	NP	−2.76**
SP	−2.64**	−1.08	0.17	0.50	SP	−1.52	−1.23	0.33	0.74	SP	−2.50**
NL vs.					NL vs.					NL vs.	
NP	−3.10**	−2.49**	−0.96	−0.84	NP	−3.33**	−1.59	0.05	0.36	NP	−2.72**
SP	−2.02**	−0.99	0.22	−0.01	SP	−1.46	0.57	1.85*	1.77*	SP	−1.33
NP vs.					NP vs.					NP vs.	
SP	1.68*	1.76*	1.15	0.65	SP	−0.68	1.63	1.31	1.02	SP	1.48
											1.74*
											1.05
											0.36

The table presents forecast comparisons based on recursive estimates, across forecasting horizons $h = 1, 3, 6$ and 12 , using the modified Diebold–Mariano statistic $DM-t$ and the Clark and West (2007) statistic $CW-t$, for the case of linear versus nonlinear models. The entries in the table show the test statistics for the null hypothesis that Model i 's forecast performance, as measured by MSPE, is not superior to that of Model j at the 5% and 10% significance levels, and vice versa (denoted by two and one asterisks respectively). See Section 3 for the model definitions.

formation (Panel A for backward looking, Panel B for forward looking, and Panel C for learning). These tables report the modified $DM-t$ statistics (Eq. (7)) and the $CW-t$ statistics (Eq. (8)) for the case of linear versus nonlinear models, as discussed in the previous section. We have named the models as follows: Model L for the linear Taylor rule, Model NL for the nonlinear Taylor rule, Model NP for the nonparametric models, and Model SP for the semiparametric ones. Table 3 provides pairwise out-of-sample forecast comparisons based on recursive estimates. The parametric models (L and NL) perform significantly better than the non- and semi-parametric models (NP and SP) over the short term horizons ($h = 1$ and 3), but such a dominance disappears as the forecast horizon lengthens. Among the parametric models, nonlinear Taylor rules are never significantly better than linear ones. Finally, semiparametric models outperform all of the others over forecast horizons $h > 3$, although they are only significantly better in two cases.

Table 4 presents the evaluation of the models under a rolling window scheme. We note that parametric models never significantly outperform semiparametric ones, and only in a couple of cases do they dominate non-parametric models. Moreover, semiparametric models perform better than the rest as the forecasting horizon lengthens, and in the particular case of forward looking expectations, significantly dominate over the forecast horizons $h > 3$. One final remark is that, under forward looking expectations, the nonlinear Taylor rules are significantly more accurate than the linear ones.¹⁸

We acknowledge that one of the limitations, and thus a criticism, of any forecasting exercise is that it is sample dependent. This has recently been pointed out by Rogoff and Stavrakeva (2008) in the context of short-horizon

exchange rate forecasting. Both the recursive and rolling results will be affected by the different sample sizes and the numbers of forecasts produced under each scheme. We have also undertaken some additional estimates and forecasts for different window sizes which we do not report here, for the sake of brevity, but discuss nonetheless.¹⁹ The number of out-of-sample observations used above (132) is complemented with sizes of 180 (in-sample: 1986–1993); 108 (in-sample: 1986–2000); and 48 (in-sample: 1986–2004) observations. The results for the different window sizes are similar, in the sense that the semiparametric model is particularly helpful for horizons longer than one. The results regarding the linear and nonlinear Taylor rules differ a bit more. In the case of the rolling scheme, as the window shortens, the nonlinear rules are more accurate than the linear ones, in general. This result is broadly intuitive, given that the SARB's instruments and policies in the most recent period of the sample can be considered to be more in line with the arguments in favor of nonlinearities described in previous sections. In this respect it is also worth noting that, as the window size decreases, the rolling forecasts for all models improve, and are sometimes more accurate than the recursive ones, on average.

Overall, our study suggests that, for the case of South Africa, it is hard to distinguish among competing forecasting models over short horizons. In the case where a single method has to be used, the semiparametric model is the most reliable for forecasts longer than one month ahead.

5. Conclusion

In this paper we examine the SARB's monetary policy reaction function by presenting both in-sample and out-of-sample results for different models or specifications of the monetary policy rule. First, we augment the 'traditional

¹⁸ The two recent studies mentioned in the introduction which use Taylor rules for forecasting interest rates, namely Qin and Enders (2008) for the US and Moura and de Carvalho (2010) for Latin America, do not test the forecast accuracies of different Taylor rules statistically. In that sense, we contribute to the literature by comparing the forecast abilities of different parametric Taylor rules. The results are not clear-cut, as the superior performance of one set of rules over another depends on the expectations formation and the sample used.

¹⁹ However, the case of the in-sample period 1986–2004 with out-of-sample observations until 2008 is extensively discussed and analysed in a working paper version of this paper, see Naraidoo and Paya (2009).

Table 4

Forecast accuracy evaluation.

Rolling estimation														
Panel A. Backward looking					Panel B. Forward looking					Panel C. Learning				
Steps ahead					Steps ahead					Steps ahead				
1	3	6	12		1	3	6	12		1	3	6	12	
L vs.					L vs.					L vs.				
NL	−1.21**	−0.67**	0.12	0.97	NL	−0.33	3.41**	4.76**	2.87	NL	−1.55**	−2.34**	−2.65**	−3.73**
NP	1.51	−0.64	−0.74	0.23	NP	1.46	−1.72*	0.37	0.81	NP	1.18	−0.53	0.31	0.23
SP	−0.27	−0.85	0.36	0.93	SP	0.99	1.63	2.95**	1.46	SP	1.00	0.56	1.00	1.08
NL vs.					NL vs.					NL vs.				
NP	2.26**	0.86	0.75	0.84	NP	1.47	−1.71*	−0.48	0.23	NP	1.81*	0.73	1.43	0.85
SP	0.41	0.52	1.52	1.17	SP	1.06	0.94	2.22**	1.56	SP	1.50	1.53	1.84*	1.37
NP vs.					NP vs.					NP vs.				
SP	−1.64*	−0.37	0.90	0.85	SP	−0.32	2.51**	2.89**	2.17**	SP	0.13	1.38	0.61	0.94

The table presents pair-wise out-of-sample forecast comparisons for the forecasting models based on fixed window rolling estimates. See the notes to Table 3.

Table A.1

Description of the variables and sources.

Variables	Description
i_t	3-month treasury bill rate
π_t	Inflation rate, computed as the annual rate of change of the consumer price index (CPI); base year: 2008 = 100, seasonally adjusted
$y_t - y^*$	Output gap, computed as the percentage deviation of the coincident business cycle indicator (computed by the SARB) from its Hodrick-Prescott trend
$I_t - I^*$	Financial indicator gap, computed as the weighted average annualised growth rate of real house prices, real share prices and the nominal exchange rate
gh_t	Annualised growth rate of the monthly real house price index (2000 = 100; CPI deflated)
gs_t	Annualised growth rate of the Johannesburg Stock Exchange (JSE) All Share Price index (2000 = 100; CPI deflated)
ge_t	Annualised growth rate of the South African rand to the US dollar

The coincident business cycle indicator is constructed at the monthly frequency by integrating various individual economic time series into a single indicator time series that mirrors the movement of the turning points in the business cycle. The time series included in the business cycle coincident indicator display various aspects of economic activity. This measure is considered to be the best proxy for output in SA at the monthly frequency, as it is more comprehensive than manufacturing, and industrial production is not available to the public.

Source: South African Reserve Bank (<http://www.reservebank.co.za>).

Taylor rule' with a financial condition index, and find that asset prices have some influence on the interest rate setting of South Africa. Second, the idea of the presence of nonlinearities in the policy rule, by which the level of response of the Reserve Bank to inflation, the output gap and financial conditions depend on the deviation of inflation from its target, is not rejected by the data. Third, forecasts constructed from semiparametric models usually perform better than the rest over the inflation targeting regime, and there are gains from such models in forecasting interest rates as the forecast horizon lengthens.

Acknowledgments

We thank the Editors and two anonymous referees for their helpful comments, and seminar participants at the University of Pretoria, participants at the African Econometric Society conference and participants at the Economic Society of South Africa conference for their valuable feedback. We have benefited greatly from discussions with Jeff Racine, who has provided us with help in coding. Ivan Paya is also grateful for financial support from the Spanish Ministerio de Educacion y Ciencia Research Project ECO-2008-05721/ECON.

Appendix

See Tables A.1 and A.2.

Table A.2

Descriptive statistics of the main variables.

	i_t	π_t	$y_t - y^*$	$I_t - I^*$	gh_t	gs_t	ge_t
Min	7.00	0.20	−7.90	−19.61	−9.67	−48.44	−39.42
Max	21.86	19	8.70	30.83	30.51	48.79	41.31
Mean	12.85	9.20	−0.10	8.01	10.36	11.58	5.70
Median	12.00	9.10	0.28	8.90	12.65	13.03	7.27
Std. dev.	3.48	4.34	2.85	8.52	7.93	19.50	14.68
Skewness	0.16	−0.02	0.05	−0.69	−0.26	−0.66	−0.64
Kurtosis	2.24	2.13	2.96	4.21	3.29	3.25	3.92

References

- Aksoy, Y., Orphanides, A., Small, D., Weiland, V., & Wilcox, D. (2006). A quantitative exploration of the opportunistic approach to disinflation. *Journal of Monetary Economics*, 53, 1877–1893.
- Bec, F., Ben Salem, M., & Collard, F. (2002). Asymmetries in monetary policy reaction function: evidence for US, French and German central banks. *Studies in Nonlinear Dynamics and Econometrics*, 6, Article 3.
- Bernanke, B., & Gertler, M. (2001). Should central banks respond to movements in asset prices? *American Economic Review*, 91, 253–257.
- Bomfimm, A., & Rudebusch, G. (2000). Opportunistic and deliberate disinflation under imperfect credibility. *Journal of Money, Credit, and Banking*, 32, 707–721.
- Busetti, F., Marcucci, J., & Veronese, G. (2009). *Comparing forecast accuracy: a Monte Carlo investigation*. Bank of Italy Working Paper 2009.
- Castro, V. (2008). *Are central banks following a linear or nonlinear (augmented) Taylor rule? The Warwick Economics Research Paper Series (TWERPS) 872*, University of Warwick, Department of Economics.
- Clarida, R., Gali, J., & Gertler, M. (1998). Monetary policy rules in practice: some international evidence. *European Economic Review*, 42, 1033–1067.

- Clarida, R., Gali, J., & Gertler, M. (2000). Monetary policy rules and macroeconomic stability: evidence and some theory. *Quarterly Journal of Economics*, 115, 147–180.
- Clark, T. (1999). Finite-sample properties of tests for equal forecast accuracy. *Journal of Forecasting*, 18, 429–450.
- Clark, T., & West, K. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics*, 138, 291–311.
- Clements, M., & Smith, J. (1997). The performance of alternative forecasting methods for SETAR models. *International Journal of Forecasting*, 3, 463–475.
- Cukierman, A., & Muscatelli, A. (2008). Nonlinear Taylor rules and asymmetric preferences in central banking: evidence from the United Kingdom and the United States. *The B.E. Journal of Macroeconomics*, 8, 977–997.
- D'Agostino, A., & Surico, P. (2009). Does global liquidity help to forecast US inflation? *Journal of Money, Credit and Banking*, 41, 479–489.
- Diebold, F., & Mariano, S. (1995). Comparing predictive accuracy. *Journal of Business and Economic Statistics*, 13, 253–263.
- Dolado, J., Maria-Dolores, R., & Naveira, M. (2005). Are monetary policy reaction functions asymmetric? *European Economic Review*, 49, 485–503.
- Gerlach-Kristen, P. (2004). Interest-rate smoothing: monetary policy inertia or unobserved variables? *Contributions to Macroeconomics*, 4, Article 3.
- Giacomini, R., & White, H. (2006). Tests of conditional predictive ability. *Econometrica*, 74, 1545–1578.
- Hall, P., Racine, J., & Li, Q. (2004). Cross-validation and the estimation of conditional probability densities. *Journal of the American Statistical Association*, 99, 1015–1026.
- Harvey, D., Leybourne, S., & Newbold, P. (1997). Testing the equality of prediction mean squared errors. *International Journal of Forecasting*, 13, 281–291.
- Hayat, A., & Mishra, S. (2010). Federal Reserve monetary policy and the nonlinearity of the Taylor rule. *Economic Modelling*, 27, 1292–1301.
- Hayfield, T., & Racine, J. (2008). Nonparametric econometrics: the np package. *Journal of Statistical Software*, 27(5), 1–32.
- Hurvich, C., Simonoff, J., & Tsai, C. (1998). Smoothing parameter selection in nonparametric regression using an improved Akaike information criterion. *Journal of the Royal Statistical Society, Series B*, 60, 271–293.
- Inoue, A., & Kilian, L. (2004). In-sample or out-of-sample tests of predictability: which one should we use? *Econometric Reviews*, 23, 371–402.
- King, M. (1996). How should central banks reduce inflation? Conceptual issues. *Economic Review Federal Reserve Bank of Kansas City*, 81, 25–52.
- Knedlik, T. (2006). Estimating monetary policy rules for South Africa. *South African Journal of Economics*, 74, 629–641.
- Layard, R., Nickell, S., & Jackman, R. (1991). *Unemployment*. Oxford: Oxford University Press.
- Li, Q., & Racine, J. (2004). Cross-validated local linear nonparametric regression. *Statistica Sinica*, 14, 485–512.
- Martin, C., & Milas, C. (2004). Modelling monetary policy: inflation targeting in practice. *Economica*, 71, 209–221.
- Martin, C., & Milas, C. (2010). Testing the opportunistic approach to monetary policy. *Manchester School*, 78, 110–125.
- McCracken, M. (2007). Asymptotics for out of sample tests of Granger causality. *Journal of Econometrics*, 140, 719–752.
- Mminele, A. (2009). Recent economic developments in South Africa. In *Remarks at the Citigroup global issues seminar*. The Ritz Carlton Hotel, Istanbul, Turkey.
- Moura, M., & de Carvalho, A. (2010). What can Taylor rules say about monetary policy in Latin America? *Journal of Macroeconomics*, 32, 392–404.
- Naraidoo, R., & Gupta, R. (2010). Modelling monetary policy in South Africa: focus on inflation targeting era using a simple learning rule. *International Business and Economics Research Journal*, 9, 89–98.
- Naraidoo, R., & Paya, I. (2009). *Forecasting monetary policy rules in South Africa*. Working paper No 200926, Department of Economics, University of Pretoria. Available from: http://web.up.ac.za/sitefiles/file/40/677/WP_2009_26.pdf.
- Nobay, A., & Peel, D. (2003). Optimal discretionary monetary policy in a model of asymmetric central bank preferences. *Economic Journal*, 113, 657–665.
- Qin, T., & Enders, W. (2008). In-sample and out-of-sample properties of linear and nonlinear Taylor rules. *Journal of Macroeconomics*, 30, 428–443.
- Robinson, P. (1988). Root-N consistent semiparametric regression. *Econometrica*, 56, 931–954.
- Rogoff, K., & Stavlakeva, V. (2008). *The continuing puzzle of short-horizon exchange rate forecasting*. NBER Working Paper 14071.
- Rudebusch, G. (2002). Term structure evidence on interest rate smoothing and monetary policy inertia. *Journal of Monetary Economics*, 49, 1161–1187.
- Stock, J., & Watson, M. (2005). *An empirical comparison of methods for forecasting using many predictors*. Working paper, Harvard University.
- Surico, P. (2007). The Fed's monetary policy rule and US inflation: the case of asymmetric preferences. *Journal of Economic Dynamics and Control*, 31, 305–324.
- Taylor, J. (1993). Discretion versus policy rules in practice. *Carnegie-Rochester Conference Series on Public Policy*, 39, 195–214.
- Walsh, C. (2009). Using monetary policy to stabilize economic activity. In *Financial stability and macroeconomic policy* (pp. 245–296). Federal Reserve Bank of Kansas City, Jackson Hole Symposium.
- West, K. (1996). Asymptotic inference about predictive ability. *Econometrica*, 64, 1067–1084.
- Woglom, G. (2003). How has inflation targeting affected monetary policy in South Africa? *South African Journal of Economics*, 71, 198–210.

Ruthira Naraidoo is a senior lecturer at the Department of Economics, University of Pretoria, South Africa. His research interests are in the areas of applied macroeconomic theory and policy, with a specialization in time series econometrics, and his focus is on topics such as unemployment, monetary policy, political economics and open economy macroeconomics.

Ivan Paya is a senior lecturer at the Department of Economics, University of Lancaster, UK. His research interests lie in the areas of time series econometrics and macroeconomics. In particular, he has analysed the application of nonlinear techniques to international economics and monetary policy.